DOCUMENT RESUME

ED 253 585 TM 850 131

AUTHOR Dunbar, Stephen B.; And Others
TITLE Simultaneous Estimation of Regression Functions for Marine Corps Technical Training Specialties.
INSTITUTION Iowa Univ., Iowa City. Cada Research Group.
SPONS AGENCY Office of Naval Research, Washington, D.C. Personnel and Training Branch.
REPORT NO ONR-TR-85-1
PUB DATE 3 Jan 85
CONTRACT N00014-83-C-0514
NOTE 43p.
PUB TYPE Reports - Research/Technical (143)

EDRS PRICE MF01/PC02 Plus Postage.
DESCRIPTORS Adults; Bayesian Statistics; Estimation (Mathematics); *Military Personnel; Military Training; *Personnel Selection; Predictor Variables; *Regression (Statistics); *Research Methodology; Vocational Aptitude; Vocational Education
IDENTIFIERS Armed Services Vocational Aptitude Battery; Marine Corps

ABSTRACT

This paper considers the application of Bayesian techniques for simultaneous estimation to the specification of regression weights for selection tests used in various technical training courses in the Marine Corps. Results of a method for m-group regression developed by Molenaar and Lewis (1979) suggest that common weights for training courses belonging to certain general categories are justified in many cases. However, such commonality of regression weights does not appear to hold for all courses in these categories--weights for some training courses remain distinct even after the application of the simultaneous estimation procedure. Thus, a hypothesis of validity generalization across training courses in a given category would only be retained for a carefully selected subset of courses and not for all groups included in the analyses. (Author)

****
* Reproductions supplied by EDRS are the best that can be made *
* from the original document. *
****

ED253585

SIMULTANEOUS ESTIMATION OF REGRESSION FUNCTIONS FOR MARINE CORPS TECHNICAL TRAINING SPECIALTIES

Stephen B. Dunbar
Shin-ichi Mayekawa
and
Melvin R. Novick

ONR Technical Report 85-1

TM 850 131

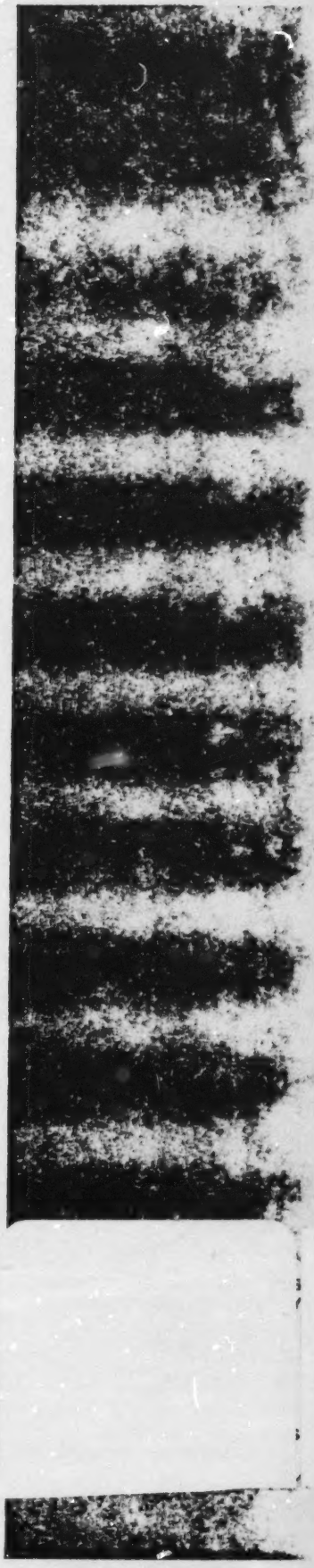
CADA RESEARCH GROUP

U.S. DEPARTMENT OF EDUCATION
NATIONAL INSTITUTE OF EDUCATION
EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)

X This document has been reproduced as received from the person or organization originating it.

☐ Minor changes have been made to improve reproduction quality.

• Points of view or opinions stated in this document do not necessarily represent official NIE position or policy.



THE UNIVERSITY OF IOWA

SIMULTANEOUS ESTIMATION OF REGRESSION FUNCTIONS FOR MARINE CORPS TECHNICAL TRAINING SPECIALTIES

Stephen B. Dunbar
Shin-ichi Mayekawa
and
Melvin R. Novick

ONR Technical Report 85-1

January 3, 1985

This research was prepared under the Office of Naval Research Contract No. N00014-83-C-0514, Melvin R. Novick, Principal Investigator, The University of Iowa, Iowa City, Iowa.

Approved for public release; distribution unlimited. Reproduction in whole or part is permitted for any purpose of the United States Government.

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: ONR Technical Report 85-1	2. GOVT ACCESSION NO.
3. RECIPIENT'S CATALOG NUMBER	
4. TITLE (and Subtitle): SIMULTANEOUS ESTIMATION OF REGRESSION FUNCTIONS FOR MARINE CORPS TECHNICAL TRAINING SPECIALTIES	5. TYPE OF REPORT & PERIOD COVERED: Technical Report, July 1, 1983 - Jan. 3, 1985
	6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s): Stephen B. Dunbar, Shin-ichi Mayekawa, Melvin R. Novick	8. CONTRACT OR GRANT NUMBER(s): N00014-83-C-0514
9. PERFORMING ORGANIZATION NAME AND ADDRESS: Melvin R. Novick, 356 Lindquist Center, The Univ. of Iowa, Iowa City, IA 52242	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: NR150-521
11. CONTROLLING OFFICE NAME AND ADDRESS: Personnel and Training Research Programs, Office of Naval Research (Code 442), Arlington, VA 22217	12. REPORT DATE: 3 January 1985
	13. NUMBER OF PAGES: 41
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office): Office of Naval Research, 536 South Clark Street, Chicago, IL 60605	15. SECURITY CLASS. (of this report): unclassified
	15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

simultaneous estimation
m-group regression
personnel selection

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This paper considers the application of Bayesian techniques for simultaneous estimation to the specification of regression weights for selection tests used in various technical training courses in the Marine Corps. Results of a method for m-group regression developed by Molenaar and Lewis (1979) suggest that common weights for training courses belonging to certain general categories are justified in many cases. However, such commonality

(continued on back)

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102-LF-014-6601

unclassified 3 January 1985
SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

of regression weights does not appear to hold for all courses in these categories--weights for some training courses remain distinct even after the application of the simultaneous estimation procedure. Thus, a hypothesis of validity generalization across training courses in a given category would only be retained for a carefully selected subset of courses and not for all groups included in the analyses.

Simultaneous Estimation of Regression Functions for Marine Corps Technical Training Specialties*

Stephen B. Dunbar
Shin-ichi Mayekawa
and
Melvin R. Novick

The University of Iowa

Abstract

This paper considers the application of Bayesian techniques for simultaneous estimation to the specification of regression weights for selection tests used in various technical training courses in the Marine Corps. Results of a method for m-group regression developed by Molenaar and Lewis (1979) suggest that common weights for training courses belonging to certain general categories are justified in many cases. However, such commonality of regression weights does not appear to hold for all courses in these categories—weights for some training courses remain distinct even after the application of the simultaneous estimation procedure. Thus, a hypothesis of validity generalization across training courses in a given category would only be retained for a carefully selected subset of courses and not for all groups included in the analyses.

*Support for this research was provided under contract #N00014-83-C-0514 with the Personnel Training Branch of the Office of Naval Research. We are indebted to Ming-mei Wang and two anonymous reviewers for comments on an earlier draft.

Simultaneous Estimation of Regression Functions for Marine Corps Technical Training Specialties

The relative value of a regression function for predicting future performance is related to its consistency of prediction in important subgroups of examinees. When large differences between predictor-criterion relationships exist for distinct subpopulations of interest, the use of a common prediction equation is questionable for a variety of reasons. This perspective reiterates a historical concern for comparisons of more than overall predictor-criterion correlations in validation research. As noted by Humphreys (1952), useful subgroup comparisons must ask whether the same score has the same meaning in the groups being compared, i.e. whether the regression lines are identical or merely parallel (p. 134). One would only add to this an obvious concern for subgroup regressions that are neither identical nor parallel.

Empirical comparisons of regression equations for subgroups defined by demographic variables such as gender and race have generally followed procedures first outlined by Gulliksen and Wilks (1950) for statistical tests of the equality of errors of estimate, slopes and intercepts. When interest focuses on regions of the predictor space where the degree of differences between regressions is acute, the Johnson-Neyman technique has also been employed (see Gamache and Novick, 1985 and Dunbar and Novick, 1985 for some recent examples). Regression comparisons performed by these techniques are perhaps well suited for settings involving a small number of groups, although they are by no means limited to such settings.

An alternative approach to accommodating differences among subgroups in regression analysis is found in the literature on central prediction systems. Procedures such as those reviewed by Linn (1966) address the

problem of making adjustments to predictor and criterion scores for individuals of varying subgroups such that overall accuracy of prediction is increased upon cross-validation. A limiting case for approaches such as these is Cleary's (1966) individual differences model for multiple regression. As discussed by Linn (1966) and others, however, empirical studies of systems for central prediction have indicated little promise--perhaps because each classical procedure posits a particular model of group differences by the nature of the adjustments that are made to predictors and criteria. Model restrictions imposed by one central prediction system may not be justified for all groups belonging to the system (Novick and Jackson, 1974) and the effectiveness of the complete system is likely to be compromised as a result. In such cases a more flexible model for prediction in the multiple-group situation is advised.

The purpose of this paper is to describe the method of Bayesian simultaneous estimation of multiple regression in m-groups and to illustrate the application of this method to the problem of specifying prediction weights for subtests of the Armed Services Vocational Aptitude Battery (ASVAB), Forms 6 and 7, in a variety of technical training specialties in the military. The general approach to this problem was first developed by Lindley (1971) and Lindley and Smith (1972), and further refined and applied by Novick, Jackson, Thayer, and Cole (1972), who demonstrated empirically the effectiveness of this method in increasing predictability. The particular model adopted in this paper is due to Molenaar and Lewis (1979), who developed it as a refinement of earlier procedures noted above. Other approaches to the problem have been implemented by Rubin (1980) and Braun, Jones, Rubin, and Thayer (1982).

Model Specification

The model for multiple regression in m-groups proposed by Molenaar and Lewis (1979), hereafter M-L, can be summarized as follows:

$$\underset{\sim}{Y}_k \sim N (\underset{\sim}{X}_{Fk} \underset{\sim}{B}_F + \underset{\sim}{X}_{Gk} \underset{\sim}{B}_{Gk}, \sigma^2 \underset{\sim}{I}_{n_k}),$$

$$k = 1, 2, \ldots, m,$$

where $\underset{\sim}{Y}_k$ = (n_k x 1) vector of observed criterion scores for group k,

$\underset{\sim}{X}_{Fk}$ = (n_k x F) matrix of predictor scores in a set F, described below,

$\underset{\sim}{X}_{Gk}$ = (n_k x G) matrix of predictor scores in a set G, described below,

$\underset{\sim}{B}_F$ = (F x 1) vector of unknown regression parameters for set F predictors,

$\underset{\sim}{B}_{Gk}$ = (G x 1) vector of unknown regression parameters for set G predictors in group k,

σ^2 = unknown residual variance for all m groups,

n_k = number of individuals in group k, and

$\underset{\sim}{I}_{n_k}$ = (n_k x n_k) identity matrix.

In addition, the unobserved parameters $\underset{\sim}{B}_F$ are said to form an exchangeable sample from F independent uniform distributions for each variable in set F. The unobserved parameters $\underset{\sim}{B}_{Gk}$ similarly form an exchangeable sample from a

$N(\underset{\sim}{\mu}_G, \gamma_G \underset{\sim}{I}_G)$ distribution. This model of prior information is further specified by designating hyperparameters $\underset{\sim}{\mu}_G$ and γ_G as exchangeable samples from U ($-\infty$, ∞) and inverse chi-square distributions with specified degrees of freedom, respectively, the latter in order to incorporate strength of prior information into the model. In the final prior specification for the M-L model, $\ln \sigma^2$ is assumed to be uniform. With the above prior specifications the joint distribution of parameters and hyperparameters given the data is determined—integrating out hyperparameters yields an expression for the joint posterior density of $\underset{\sim}{B}_F$, $\underset{\sim}{B}_{Gk}$ and σ^2 from which Molenaar and Lewis obtain joint modal estimates.

The M-L model for regression in m-groups represents a general simplification of previous Bayesian solutions to the problem developed by Lindley (1971) and Lindley and Smith (1972). In particular, the M-L specification differs from the original formulations in three important ways: (1) a partitioning of predictor variables into disjoint sets, (2) a restriction on the prior between-group covariance matrix of the regression parameters to diagonality, and (3) a specification of a non-informative prior distribution on a <u>common</u> residual variance for all groups. The implications of each difference for regression in m-groups are discussed below. These features and other numerical aspects of the M-L algorithm lead to an accurate and computationally efficient method for simultaneous estimation of multiple regression in m-groups.

Regression coefficients in the M-L model are of two types, common or fixed across groups (the $\underset{\sim}{B}_F$) and variable across the k groups (the $\underset{\sim}{B}_{Gk}$). Variables are assigned to sets F and G on the basis of the between-group

variances of their estimated regression coefficients. When prior information strongly suggests that between-group variability is negligible, a predictor is assigned to set F at the outset of the estimation procedure. Otherwise, predictors are initially assigned to set G and are transferred to set F only if the estimates of between-group variance fall below a threshold value during the iterative solution. Molenaar and Lewis (1979) describe how such estimates are obtained and used to partition predictors.

In addition to circumventing certain problems in estimation that have occurred with previous implementations of m-group regression models, the partition of predictors explicitly recognizes that some predictors perform in a virtually identical fashion across groups. Novick, Jackson, Thayer and Cole (1972) describe the Lindley-Smith model as one which seeks a compromise between within-group least squares and pooled least-squares analyses. Partitioning predictors into those with fixed and free parameters allows for pooling in a portion of the model when data and/or prior information suggest such pooling to be appropriate. Indeed, when predictor set G is empty, the model reduces to a pooled analysis, whereas when set F is empty the model is equivalent to that of Lindley and Smith (1972).

A second feature of the M-L model that distinguishes it from previous approaches is the assumption of independent prior distributions for the parameters $\underset{\sim}{B}_F$ and $\underset{\sim}{B}_{Gk}$. Restricting the dispersion matrix for the $\underset{\sim}{B}_{Gk}$ to being diagonal places rather strong demands on the predictor set and is likely to be more appropriate for some predictor sets than for others. As noted by Molenaar and Lewis, however, prior knowledge about covariances is likely to be minimal in many practical situations - they also observe that their model allows for such covariances in the posterior distribution. A

consequence of this aspect of the model is that lack of shrinkage toward a common value across groups for, say, β_{1k} will not influence the degree of shrinkage that takes place for coefficients of other independent variables. This is perhaps reasonable for a selection battery that is heterogeneous with respect to the abilities required for test performance, such as the subtests of ASVAB.

The third aspect of the M-L model that distinguishes it from previous approaches is an assumption of between-group homoscedasticity of residual variances. This too places stronger demands on data, but for groups which are truly exchangeable such an assumption may be no less unreasonable than the usual assumption of homogeneity of variances within-groups. Indeed, it was observed by a reviewer that homogeneity of residual variances between groups in the M-L approach is likely to be a serious oversimplification in practice only when strong prior information for this aspect of the model is available. When the scaling of the dependent variable is arbitrary, simple standardization within groups, as is done in the following analysis, also helps to justify this aspect of the M-L model.

Method

Data Source

The M-L model for m-group regression was used to investigate predictor-criterion relationships in a set of technical training data from the Marine Corps. The particular data used were previously analyzed by Sims and Hiatt (1981) and consist of validation records for training courses taken from general categories of military job specialties. Of special interest is the

extent to which the regressions of final course grade (FCG) in training on a relevant set of predictors from ASVAB are similar for a group of training courses considered to be exchangeable. This is a special concern for a heterogeneous selection battery like ASVAB. A question that has plagued users of ASVAB over the years is whether common weights for subtests are justified for training programs with similar content. By initially considering such programs exchangeable, an alternative assessment of differences between regression equations for subgroups can be made. The general categories of specialties considered in this analysis are classified as Clerical, Electrical, and Mechanical. Individual recruits are assigned to training courses on the basis of ASVAB composite scores that are determined from the predictors used in each category of specialties.

Data Analysis

The training courses belonging to Clerical, Electrical and Mechanical specialty areas are presented in Table 1, along with sample sizes for each group. Preliminary inspections of bivariate scatterplots of course grades and ASVAB subtests were made for each training course in order to identify any serious departures from linearity and homoscedasticity within groups and to detect outliers. For several training courses, a small number of outliers were detected in the distribution of course grades—such observations were deleted in the ensuing analyses on the grounds that final grades for certain low-performing recruits were arbitrarily determined (see Sims and Hiatt, 1981).

For each category of training specialties, then, data analysis consisted of initial least-squares regressions of FCG on the relevant set of ASVAB predictor variables. These within-group least squares results were

then used as starting values in the M-L simultaneous estimation procedure. All courses listed in a given category in Table 1 were considered exchangeable in the Bayesian analysis. Thus, nine courses were analyzed simultaneously for the Clerical area, six for the Electrical area, and eleven for the Mechanical area.

Insert Table 1 About Here

The prior information required by the M-L model was specified in the same manner for the three types of specialties. In particular, prior estimates of the between-group variance of the parameters $\underset{\sim}{B}_{Gk}$ were obtained from the so-called Model II analysis in a manner described by Jackson (1972). In essence, this method treats the β'_{gk} and their standard errors from the least squares analysis in a random-effects ANOVA manner in order to derive estimates of the between-group variance of β_{gk} for g = 1, 2, ..., G. These values, γ'_g, were then treated as modal estimates from an inverse chi-square distribution, with degrees of freedom equal to 1 to indicate minimal prior information concerning between-group variability in the parameters.

In addition to the separate regression analyses described above, an attempt to understand the behavior of the M-L esitmates in future samples was made through a cross-validation study of the Mechanical specialties. In this analysis, a 25 percent random sample was obtained from each training course and used to estimate parameters by least-squares and M-L methods. The estimates obtained from these samples were used in predicting course grades of recruits in the remaining 75 percent. It should be clear that this procedure does not mirror exactly an ideal cross-validation study.

Nevertheless, it does provide a beginning to understanding how the M-L estimation procedure might be expected to perform in practice, especially for training programs with sample sizes that would otherwise prohibit separate least-squares solutions.

Results

The principal results presented are the estimates of regression parameters based on least-squares and M-L m-group analyses. The dependent variable, FCG, has been standardized within-groups to remove apparent differences between training courses in grading standards from the criterion distributions. The independent variables, ASVAB subtests, are typically reported on scales ranging from 20 to 80 and exceptions to this are noted in the description of results.

Clerical Specialties

ASVAB subtests used in the selection composite for clerical specialties include ability tests of Arithmetic Reasoning (AR), Word Knowledge (WK), Attention-to-Detail (AD), and an attitudinal measure called the Attentiveness Scale (CA). Unlike scores for the ability measures, observed scores on CA can range from 0 to 20. The results of within-group least-squares, pooled least-squares, and M-L analyses are summarized in Table 2. Estimates of coefficients for the four independent variables appear under the appropriate column heading. Rather than reporting the estimated intercept at 0, which is out of range on the joint predictor distribution, the intercept at the pooled centroid of the predictors is reported under the

heading Int(C). This value allows a more suitable comparison of any intercept differences that may exist among the groups. The residual standard deviations for the least-squares analysis appear in the column marked Res SD.

The within-group least-squares results in Panel (a) show clear differences among the groups, both with respect to intercept and slopes of the regression surfaces. Notable features of these results include the pattern of positive and negative intercepts across groups and the weights of relatively small magnitude for AD (recall AD is scaled in the same way as are AR and WK). In addition, coefficients estimated for the attitudinal measure, CA, display marked variation among the groups. However, when one considers that typical standard deviations on this measure are 2.5 to 3 points, the contributions made by it to prediction are quite small. Indeed, the usual significance tests failed to reject the null hypothesis that the coefficients for both AD and CA were zero at the .05 level for all Clerical specialties. Nevertheless, these variables were included in the m-group analyses in part to monitor the extent to which between-group differences on these variables were due to sampling fluctuations. Although not included in the table, multiple correlations in the least-squares analysis ranged from .40 to .79 within groups (.59 in the pooled sample).

Insert Table 2 About Here

The results of the M-L analyses in Panel (b) indicate a high degree of similarity among the Clerical training courses in terms of the slopes of regression surfaces using an equation with all four predictors when the courses are considered exchangeable and vague prior information is

specified. Estimates of coefficients for AR and WK do not differ to any important degree across the nine specialties and the apparently large differences observed for coefficients of CA in the least squares analysis are seen as a consequence of sampling variation through the eyes of the Bayesian approach. Though not reported here, results for the M-L model with predictors AD and CA removed were very similar to those in Panel (b), with only a small increase in the residual SD estimate caused by the reduced predictor set.

Where clerical specialties do differ, even in the M-L solution , is in their intercepts at the pooled centroid. Application of the M-L model didn't greatly influence the intercept differences noted in the least squares solutions. Aside from this factor, the ASVAB subtests used for clerical specialties perform quite consistently in predicting course grades. Justification for differential weighting of predictors among training courses would apparently have to come from an assumption that some courses are not exchangeable in the way specified by the M-L model.

Electrical Specialties

ASVAB subtests used in selection for courses classified as electrical specialties were AR, General Science (GS), Mathematics Knowledge (MK), and Electrical Information (EI). Results of regression analyses from the various approaches are given in Table 3, the contents of which parallel those of the previous table.

The least-squares estimates for Electrical specialties show greater variation among groups than was seen in the case of Clerical specialties. Multiple correlations for this group of specialties ranged from .15 to .58 (.37 in the pooled sample). Differences between groups are particularly

noticeable for coefficients of AR, which are relatively large for Avionics Repair, Basic Electrician and Basic Electronics, and near zero for the remaining courses. Moreover, the least-squares coefficient for MK in the Basic Electronics group is much larger (.047) than it is in any other group. In contrast to results from the Clerical specialties, no single predictor variable in the least-squares analysis appears less important than the others in predicting performance, at least based on the magnitudes of the regression weights. Again, because the immediate purpose here is not variable selection, all subtests are retained for the M-L analysis.

Insert Table 3 About Here

The M-L results in Panel (b) again show regression toward a common value for many of the coefficients in the model used with Electrical specialties. One predictor, AR, shows much greater homogeneity across groups--the Bayesian estimates of weights for this variable are also quite different in some cases from the pooled least-squares weights given in Panel (a). Note also that the weight for the Electrical Information test (EI) was judged constant across groups using the Model II prior estimates of between-group variances. A contrast to this degree of homogeneity is observed with respect to predictors GS and MK. Estimated weights of the former range from .014 to .021, while those of the latter are around .026 for all but the Basic Electronics course, whose estimated weight under the M-L model was .046. As seen in the results for Clerical specialties, intercepts for the six Electrical training courses are quite distinct when evaluated at the centroid of the pooled distributions. With small mean differences on the

predictors known to exist for these groups, this again is an unsurprising result.

Although estimates of slopes for the six Electrical specialties were quite similar for two predictors, even the M-L results fail to justify a single prediction equation for all specialties in this category. Predicting success for the Basic Electronics group using this set of predictors clearly requires heavier weight to be placed on MK. Whether such a result is taken to mean that Basic Electronics is not exchangeable with the other Electrical specialties is perhaps open to question. The M-L results indicate that even when exchangeability is assumed a priori, the data warrant that a prediction model for this course be considered separately from those of other Electrical specialties.

Mechanical Specialties

The ASVAB subtests that belong to the selection composite for mechanical specialties are again AR and GS, used previously, a test of Mechanical Comprehension (MC) and a test of Automotive Information (AI). Results of the regression analyses using these subtests as predictors are given in Table 4.

Variation from group to group in the magnitudes of least-squares regression weights is again the rule rather than the exception for the Mechanical specialties. With respect to GS, weights are near zero for the Aviation Crash Crew and Small Arms Repair courses, yet of substantial magnitude, relatively speaking, for ASM (Structures) and Tracked Vehicle Repair (.034 and .043, respectively). The other predictor in this set that displays marked variation in weights across groups is AI, which has a near zero weight for ASM (Safety) and a clearly non-zero weight for the two automotive

mechanics training courses. The magnitudes of weights assigned to AR and MC are much more homogeneous in the least-squares analyses -- indeed, the estimate given for MC the pooled sample is quite representative of nearly all within-group estimates. The pattern of positive and negative intercepts at the pooled centroid is again seen in the results for mechanical specialties, as is some variability in the size of the standard errors of estimate. Multiple correlations for these groups ranged from .34 to .67, with a value of .50 obtained in the pooled sample.

Insert Table 4 About Here

Shrinkage of parameter estimates toward common values in the M-L approach is again observed in the results in Panel (b) of Table 4. Two variables (AR and MC) were assigned to predictor set F on the basis of prior specifications determined from the Model II analysis. However, the M-L estimates of parameters for predictors GS and AI have only moderately approached a value that is common across groups. Although the coefficient for GS in the Tracked Vehicle Repair course has become closer in value to those of other courses, weights for GS are still comparatively small in the Crash Crew and Small Arms Repair courses. Moreover, GS appears to play a more prominent role in predicting course grades in the Advanced Auto course than it does in the Basic Auto course. These differences were still manifest when prior specifications were altered to indicate that more weight should be placed on the Model II analysis. Given the strong assumptions of the M-L model, differences like these would be difficult to ignore in future specifications of prediction equations for these courses. Other between-group differences that remain even after application of the M-L approach

involve estimates of intercepts and of weights for AI, which remain larger for the two automotive training courses.

Cross Validation

An additional concern when results of a series of analyses like those in this report are to be used for future versions of an aptitude battery is the expected stability of regression coefficients on cross-validation. The issues relevant to this question have received much attention in the literature over the years and no review will be given here. Bayesian methods for simultaneous estimation of regression coefficients have been shown to cross-validate better than within-group least-squares (cf. Novick, Jackson, Thayer and Cole, 1972), particularly with small sample sizes. This result was confirmed for the Molenaar-Lewis approach with the limited cross-validation study performed on data from the Mechanical specialties. Table 5 contains mean-squared errors (MSE) and correlations (CORR) between observed and predicted criterion scores from the cross-validation analysis. The results in Table 5 are generally consistent with past comparisons of Bayesian m-group techniques and conventional methods -- a small yet consistent trend toward smaller errors of prediction on cross-validation using a Bayesian m-group model. Although the differences between least-squares and M-L errors given in Table 5 are quite small -- absolute differences between MSE's ranging from .001 to .043 -- this is perhaps to be expected when the cross-validation sample represents data from the same year as the calibration sample. If one goal of the Bayesian method is to smooth out minor temporal fluctuations in the parameter estimates that might otherwise be interpreted as differences between groups, then one would expect greater accuracy on cross-validation for the M-L estimates and data from a subsequent year.

That the results using a 25/75 split of data from one year are in the correct direction suggests some promise in further applications of the m-group approach to data of the type considered in this analysis.

Insert Table 5 About Here

Discussion

Application of the M-L model for m-group regression to the prediction of success in technical training generally supports the use of common weights when ASVAB subtests are used to construct selection composites. If one were to place heavy reliance on the results of the within-group least-squares analyses, a different conclusion would certainly follow from a simple examination of estimated coefficients, even with sample sizes as large as those available in this data set. To the extent that the assumption of exchangeability is satisfied by the groups analyzed simultaneously, the M-L results provide a useful alternative assessment of the differences between specific training programs with similar content. These differences were found to be negligible for the group of Clerical training programs considered, but of sufficient magnitude for certain Electrical and Mechanical specialties to warrant more careful consideration when selection composites for future versions of ASVAB are developed.

A consideration of utmost importance in evaluating the appropriateness of the M-L model for developing prediction equations for technical training specialties in the military is the question of exchangeability. The approach to the question adopted in this paper has been to assume

exchangeability among training courses on the basis of course content and to allow results to point to groups which might well be distinct. Deletion of the few specialties in the Electrical and Mechanical areas that seem atypical of the area at large would no doubt produce even greater homogeneity of regression coefficients for predictors than has been reported here. However, more experience in applying the M-L method, or similar methods, to data from other recruiting years is likely to provide a better check on the extent to which exchangeability is justified for the groups studied in this analysis. In general, it seems that this type of assumption is properly evaluated over time rather than at a specific point in time.

The choice of the Molenaar-Lewis model for m-group regression also receives some support from the cross-validation results. As observed in the description of the model, M-L places greater restrictions on the specification of prior information, in part to increase computational efficiency and to avoid certain estimation problems (Molenaar and Lewis, 1979, pp. 6ff.). These restrictions do not appear to have compromised the effectiveness of the model for technical training specialties in the Marine Corps. Whether or not a model with more detailed prior specifications would yield results that differ perceptibly from those of the M-L approach is an open question -- the extent of improvement would certainly be related to the strength of that additional prior information. It is far from obvious that strong prior information concerning, for example, between-group covariances of regression parameters or between-group variances of residual standard deviations is available for military training specialties at the present time. Further study of such specialties using m-group techniques should certainly consider applying more detailed prior specifications and methods of estimating the required hyperparameters. Some informal comparisons made with data of the

type used in this study indicate M-L yields results similar to those from a refinement of Rubin's (1980) empirical-Bayes approach when the M-L analysis is performed after standardizing the criterion variable within groups.

Conclusion

Application of the Molenaar-Lewis model for regression in m-groups to the problem of predicting training success in various Marine Corps job specialties indicates some justification for limited use of common weights for predictor variables in training courses considered exchangeable on a priori grounds. All groups in the Clerical area were characterized by slopes of similar magnitude, although intercept differences were common. For both Electrical and Mechanical specialty areas, training courses were identified that had estimated slopes differing markedly with respect to at least one of the predictor variables included. Continued monitoring of such courses is important in judging the appropriateness of a common prediction equation for all training programs in these two areas.

The relevance of the methodology of m-group regression to predicting success in a variety of military training programs is an important outcome of this analysis. The extreme views of complete generalization of the criterion-related validity of ASVAB subtests across all courses and of entirely course-specific characterizations of subtest validity are equally unattractive. The model for m-group regression used in this study allows an assessment of exactly where between these two extreme positions an accurate characterization of criterion-related validity lies.

References

Braun, H. I., Jones, D. H., Rubin, D. B., and Thayer, D. T. (1983). Empirical Bayes estimation of coefficients in the general linear model from data of deficient rank. Psychometrika, 48, 171-181.

Cleary, T. A. (1966). An individual differences model for multiple regression. Psychometrika, 31, 215-224.

Dunbar, S. B. and Novick, M. R. (1985). Predicting success in training for males and females: Marine Corps clerical specialties and ASVAB Forms 6 and 7. (ONR Technical Report 85-2). Iowa City, IA: College of Education, The University of Iowa.

Gamache, L. M. and Novick, M. R. (1985). Choice of variables and gender-differentiated prediction within selected academic programs. Journal of Educational Measurement, in press.

Gulliksen, H. and Wilks, S. S. (1950). Regression tests for several samples. Psychometrika, 15, 91-114.

Humphreys, L. G. (1952). Individual differences. In C. P. Stone and D. W. Taylor (Eds.), Annual Review of Psychology. Stanford, CA: Annual Reviews, 131-150.

Jackson, P. H. (1972). Simple approximations in the estimation of many parameters. British Journal of Mathematical and Statistical Psychology, 25, 213-228.

Lindley, D. L. (1971). The estimation of many parameters. In V. P. Godambe and D. A. Spratt (Eds.), Foundations of Statistical Inference. Toronto, Canada: Holt, Rinehard and Winston, 435-455.

Lindley, D. L. and Smith, A. F. M. (1972). Bayesian estimates for the linear model. Journal of the Royal Statistical Society (Series B), 34, 1-41.

Linn, R. L. (1966). Grade adjustments for the prediction of academic performance: A review. Journal of Educational Measurement, 3, 313-329.

Molenaar, I. W. and Lewis, C. (1979). An improved model and computer program for Bayesian m-group regression. (ONR Technical Report No. 79-5). Iowa City, IA: College of Education, The University of Iowa.

Novick, M. R., Jackson, P. H., Thayer, D. T. and Cole, N. S. (1972). Estimating multiple regression in m-groups: A cross-validation study. British Journal of Mathematical and Statistical Psychology, 25, 33-50.

Novick, M. R. and Jackson, P. H. (1974). Further cross-validation analysis of the Bayesian m-group regression method. American Educational Research Journal, 11, 77-85.

Rubin, D. B. (1980). Using empirical Bayes techniques in the law school validity studies. Journal of the American Statistical Association, 75, 801-816.

Sims, W. H. and Hiatt, C. M. (1981). Validation of the Armed Services Vocational Aptitude Battery (ASVAB) Forms 6 and 7 with Appications to ASVAB Forms 8, 9, and 10. (CNA Report 1160). Alexandria, VA: Center for Naval Analysis.

Table 1

Sample Sizes for Marine Corps
Specialty Areas

Specialty Area	Sample Size
Clerical	
Basic Supply Stock	1238
Personal Financial Records	375
Administrative	1336
Personnel	176
Unit Diary	149
Communications Center	711
Aviation Operations	247
Aviation Maintenance Administration	215
Aviation Supply	496
Electrical	
Basic Electrician	223
Electrical Equipment Repair	215
Basic Electronics	1093
Radio Fundamentals	165
Field Radio Operator	1244
Avionics Repair	297
Mechanical	
Basic Auto Mechanic	1276
Advanced Auto Mechanic	618
Combat Engineer	934
Engineering Equipment Mechanic	691
Tracked Vehicle Repair	233
Basic Helicopter	801
ASM* (Safety)	124
ASM* (Hydraulics)	563
ASM* (Structures	611
Aviation Crash Crew	295
Small Arms Repair	323

*ASM = Aviation Structural Mechanics.

Table 2

Least-squares and M-L m-group Estimates of
Regressions for Clerical Specialties

Panel (a) - Least-squares

Training Course	Int(C)*	AR	WK	AD	CA	Res SD
Basic Supply	-.024	.048	.027	.004	.039	.862
Fin. Records	-.107	.050	.019	.002	.036	.620
Administrative	-.036	.032	.027	.009	.044	.754
Personnel	-.105	.043	.037	.003	.067	.869
Unit Diary	-.217	.026	.046	.003	.067	.908
Comm. Center	.152	.030	.027	.003	.031	.685
Av. Operations	.107	.036	.009	.017	.006	.928
Av. Maintenance	.088	.047	.027	.005	.016	.903
Av. Supply	.175	.039	.031	.015	.015	.890
Pooled	.000	.036	.026	.007	.033	.811

Panel (b) - Molenaar-Lewis

Training Course	Int(C)*	AR	WK	AD	CA
Basic Supply	-.015	.041	.028	.006	.037
Fin. Records	-.089	.039	.026	.007	.034
Administrative	-.028	.036	.027	.008	.039
Personnel	-.052	.039	.027	.007	.037
Unit Diary	-.124	.038	.027	.007	.036
Comm. Center	.151	.036	.027	.006	.033
Av. Operations	.102	.038	.025	.008	.029
Av. Maintenance	.073	.039	.027	.007	.032
Av. Supply	.154	.039	.027	.009	.030
Modal Estimate of Res SD = .803					

*Int(C) represents the value of the regression intercept at the centroid of the predictors in the pooled sample

Table 3

Least-squares and M-L m-group Estimates of
Regressions for Electrical Specialties

Panel (a) - Least-squares

Training Course	Int(C)	AR	GS	MK	EI	Res SD
Basic Electrician	.228	.019	.014	.023	.026	.930
Elec. Equip. Repair	-.113	.007	-.004	.031	.018	.968
Basic Electronics	-.354	.019	.022	.047	.021	.813
Radio Fundamentals	-.385	.009	.030	.026	.012	.965
Field Radio Operator	.299	.009	.017	.028	.017	.914
Avionics Repair	-.436	.035	.025	.012	.034	.922
Pooled	.000	.003	.013	.027	.014	.931

Panel (b) - Molenaar-Lewis

Training Course	INT(C)	AR	GS	MK	EI*
Basic Electrician	.212	.015	.018	.026	.020
Elec. Equip. Repair	-.144	.014	.014	.026	.020
Basic Electronics	-.329	.015	.021	.046	.020
Radio Fundamentals	-.387	.014	.019	.027	.020
Field Radio Operator	.314	.014	.016	.026	.020
Avionics Repair	-.318	.015	.021	.025	.020
Modal Estimates of Res. SD = .888					

*EI was judged to belong to set F using the Model II prior estimate of between-group variance.

Table 4

Least-squares and M-L m-group Estimates of Regressions for Mechanical Specialties

Panel (a) - Least-squares

Training Course	Int(C)	AR	GS	MC	AI	Res SD
Basic Auto	-.111	.028	.017	.018	.038	.788
Advanced Auto	-.134	.029	.028	.025	.034	.746
Combat Engineer	.265	.030	.021	.027	.017	.785
Eng. Equip. Mech.	.329	.022	.020	.019	.029	.861
Trk. Veh. Repair	.010	.028	.043	.017	.016	.831
Basic Helicopter	-.212	.022	.022	.020	.025	.872
ASM (Safety)	-.378	.032	.018	.020	.006	.942
ASM (Hydraulics)	-.122	.028	.029	.026	.019	.880
ASM (Structures)	-.180	.019	.034	.018	.013	.909
Av. Crash Crew	.091	.031	.004	.015	.018	.922
Small Arms	.113	.028	.002	.022	.015	.900
Pooled	.000	.020	.018	.020	.023	.868

Panel (b) - Molenaar-Lewis

Training Course	Int(C)	AR	GS	MC*	AI
Basic Auto	-.103	.026	.018	.021	.035
Advanced Auto	-.121	.026	.029	.021	.032
Combat Engineer	.256	.026	.024	.021	.020
Eng. Equip. Mech.	.342	.026	.019	.021	.026
Trk. Veh. Repair	-.015	.026	.032	.021	.020
Basic Helicopter	-.217	.026	.021	.021	.024
ASM (Safety)	-.334	.026	.018	.021	.017
ASM (Hydraulics)	-.113	.026	.028	.021	.021
ASM (Structures)	-.185	.026	.028	.021	.016
Av. Crash Crew	.090	.026	.010	.021	.018
Small Arms	.118	.026	.009	.021	.017
	Modal Estimate of Residual SD = .841				

*Variable assigned to set F on basis of Model II prior estimates of between-group variances.

Table 5

Mean Square Errors and Correlations from Cross-Validation Analyses for Mechanical Specialties

Training Course		MSE	CORR
Basic Auto	LS	.6272	.6111
	ML	.6282	.6103
Advanced Auto	LS	.6157	.6210
	ML	.6031	.6310
Combat Engineer	LS	.6081	.6268
	ML	.6010	.6324
Eng. Equip. Mech.	LS	.7535	.4979
	ML	.7385	.5127
Trk. Veh. Repair	LS	.7326	.5212
	ML	.6992	.5522
Basic Helicopter	LS	.7620	.4891
	ML	.7407	.5104
ASM (Safety)	LS	.8554	.3525
	ML	.8447	.4055
ASM (Hydraulics)	LS	.7876	.4630
	ML	.7698	.4818
ASM (Structures)	LS	.8663	.3682
	ML	.8395	.4027
Av. Crash Crew	LS	.8875	.3409
	ML	.8443	.3990
Small Arms	LS	.8404	.4036
	ML	.8326	.4132

Navy

1 CDR Robert J. Biersner
Naval Medical R&D Command
National Naval Medical Center
Bethesda, MD 20814

1 Dr. Nick Bond
Office of Naval Research
Liaison Office, Far East
APO San Francisco, CA 96503

1 Lt. Alexander Bory
Applied Psychology
Measurement Division
NAMRL
NAS Pensacola, FL 32508

1 Dr. Stanley Collyer
Office of Naval Technology
800 N. Quincy Street
Arlington, VA 22217

1 Dr. Charles E. Davis
Personnel and Training Research
Office of Naval Research (Code 442PT)
800 North Quincy Street
Arlington, VA 22217

1 Dr. Richard Elster
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

1 Mr. Paul Foley
Navy Personnel R&D Center
San Diego, CA 92152

1 Mr. Dick Hoshaw
NAVOP-135
Arlington Annex
Room 2834
Washington , DC 20350

1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis (75)
Millington, TN 38054

1 Dr. William L. Maloy (02)
Chief of Naval Education and Training
Naval Air Station
Pensacola, FL 32508

Navy

1 Dr. Kneale Marshall
Chairman, Operations Research Dept.
Naval Post Graduate School
Monterey, CA 93940

1 Dr. James McBride
Navy Personnel R&D Center
San Diego, CA 92152

1 Cdr Ralph McCumber
Director, Research & Analysis Division
Navy Recruiting Command
4015 Wilson Boulevard
Arlington, VA 22203

1 Dr. George Moeller
Director, Behavioral Sciences Dept.
Naval Submarine Medical Research Lab
Naval Submarine Base
Groton, CT 06349

1 Library, Code P201L
Navy Personnel R&D Center
San Diego, CA 92152

1 Technical Director
Navy Personnel R&D Center
San Diego, CA 92152

6 Commanding Officer
Naval Research Laboratory
Code 2627
Washington, DC 20390

1 Psychological Sciences Division
Code 442
Office of Naval Research
Arlington, VA 22217

1 Organizational Effectiveness
Research Group, Code 4420E
Office of Naval Research
Arlington, VA 22217

6 Personnel & Training Research Group
Code 442PT
Office of Naval Research
Arlington, VA 22217

1 Office of the Chief of Naval Operations
Research Development & Studies Branch
OP 115
Washington, DC 20350

BEST COPY AVAILABLE

Navy

1 LT Frank C. Petho, MSC, USN (Ph.D)
CNET (N-432)
NAS
Pensacola, FL 32508

1 Dr. Bernard Rimland (01C)
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Carl Ross
CNET-PDCD
Building 90
Great Lakes NTC, IL 60088

1 Mr. Drew Sands
NPRDC Code 62
San Diego, CA 92152

1 Lt. Marybeth Schnable
COMNAVCRUITCOM
Code 215
4015 Wilson Blvd
Arlington, VA 22206

1 Dr. Robert G. Smith
Office of Chief of Naval Operations
OP-987H
Washington, DC 20350

1 Dr. Alfred F. Smode, Director
Department N-7
Naval Training Equipment Center
Orlando, FL 32813

1 Dr. Richard Snow
Liaison Scientist
Office of Naval Research
Branch Office, London
Box 39
FPO New York, NY 09510

1 Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Frederick Steinheiser
CNO - OP115
Navy Annex
Arlington, VA 20370

1 Mr. Brad Sympson
Navy Personnel R&D Center
San Diego, CA 92152

Navy

1 Dr. James Tweeddale
Technical Director
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Frank Vicino
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152

1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

1 Mr John H. Wolfe
Navy Personnel R&D Center
San Diego, CA 92152

1 Capt. Bruce Young
COMNAVCRUITCOM
Code 21
4015 Wilson Blvd
Arlington, VA 22206

1 Cadr. Joe Young
HQ, MEPCOM
ATTN: MEPCT-P
2500 Green Bay Road
North Chicago, IL 60064

Marine Corps

1 Capt. Rick Butler
CAT Project Office
HQ, Marine Corps
Washington, DC 20380

1 Mr. Paul DiRenzo
Commandant of the Marine Corps
Code LBC-4
Washington, DC 20380

1 H. William Greenup
Education Advisor (E031)
Education Center, MCDEC
Quantico, VA 22134

1 Maj. John Keene
ADP Systems Branch
C3 Development Center (D104)
MCDEC
Quantico , VA 22134

1 Jerry Lehnus
CAT Project Office
HQ Marine Corps
Washington , DC 20380

1 Col. Ray Leidich
Headquarters, Marine Corps
MPI
Washington, DC 20380

1 Director, Office of Manpower Utilizatio
HQ, Marine Corps (MPU)
BCB, Bldg. 2009
Quantico, VA 22134

1 Headquarters, U. S. Marine Corps
Code MPI-20
Washington, DC 20380

1 Lt. Col. Jim Murphy
HQ, Marine Corps
Code MRRP
Washington, DC 20380

1 Special Assistant for Marine
Corps Matters
Code 100M
Office of Naval Research
800 N. Quincy St.
Arlington, VA 22217

Marine Corps

1 DR. A.L. SLAFKOSKY
SCIENTIFIC ADVISOR (CODE RD-1)
HQ, U.S. MARINE CORPS
WASHINGTON, DC 20380

1 Major Frank Yohannan, USMC
Headquarters, Marine Corps
(Code MPI-20)
Washington, DC 20380

BEST COPY AVAILABLE

Army

1 Technical Director
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Kent Eaton
Army Research Institute
5001 Eisenhower Blvd.
Alexandria , VA 22333

1 Lt. Col Rich Entlich
HQ, Dept. of the Army
OCSA(DACS-DPM)
Washington, DC 20310

1 Dr. Beatrice J. Farr
U. S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Myron Fischl
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Lt. Col. Ron Harmer
USARCRO-RS
Ft. Sheridan, IL 60037

1 Dr. Milton S. Katz
Training Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Clessen Martin
Army Research Institute
5001 Eisenhower Blvd.
Alexandria, VA 22333

1 Dr. William E. Nordbrock
FMC-ADCO Box 25
APO, NY 09710

1 Mr. Robert Ross
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Army

1 Mr. Lou Ruberton
DAPE-MPA-C3
Department of the Army
Washington, DC 20310

1 Dr. Joyce Shields
Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Ms. Betty Stickel
DAPE-MFA-P
2B729 Pentagon
Washington, DC 20310

1 Dr. Hilda Wing
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

BEST COPY AVAILABLE

Air Force

1 Air Force Human Resources Lab
AFHRL/MPD
Brooks AFB, TX 78235

1 Technical Documents Center
Air Force Human Resources Laboratory
WPAFB, OH 45433

1 U.S. Air Force Office of Scientific Research
Life Sciences Directorate, NL
Bolling Air Force Base
Washington, DC 20332

1 Air University Library
AUL/LSE 76/443
Maxwell AFB, AL 36112

1 Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks AFB, TX 78235

1 Col. Roger Campbell
AF/MPXOA
Pentagon, Room 4E195
Washington, DC 20330

1 Mr. Raymond E. Christal
AFHRL/MOE
Brooks AFB, TX 78235

1 Dr. Alfred R. Fregly
AFOSR/NL
Bolling AFB, DC 20332

1 Dr. Genevieve Haddad
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

1 Dr. Patrick Kyllonen
AFHRL/MOE

Brooks AFB, TX 78235

1 Mr. Randolph Park
AFHRL/MOAN
Brooks AFB, TX 78235

1 Lt. Col. Dave Payne
AFHRL/MOE
Brooks AFB, TX 78235

Air Force

1 Dr. Roger Pennell
Air Force Human Resources Laboratory
Lowry AFB, CO 80230

1 Dr. Malcolm Ree
AFHRL/MP
Brooks AFB, TX 78235

1 Maj. Bill Strickland
AF/MPXOA
4E168 Pentagon
Washington, DC 20330

1 Lt. Col James E. Watson
HQ USAF/MPXOA
The Pentagon
Washington, DC 20330

1 Major John Welsh
AFHRL/MOAN
Brooks AFB , TX

BEST COPY AVAILABLE

Department of Defense

1 Mr. Bob Brandewie
Defense Manpower Data Center
550 Casino El Estisro, #200
Monterey, CA 93940

1 Mr. J. Burgener
MEPCOM
MEPCT-P
2500 Green Bay Road
North Chicago, IL 60064

1 LCmdr. Tom Dean
HQ, MEPCOM
MEPCAM-P
2500 Green Bay Road
North Chicago , IL 60064

12 Defense Technical Information Center
Caseron Station, Bldg 5
Alexandria, VA 22314
Attn: TC

1 Dr. William Grahae
Testing Directorate
MEPCOM/MEPCT-P
Ft. Sheridan, IL 60037

1 Dr. Clarence McCormick
HQ, MEPCOM
MEPCT-P
2500 Green Bay Road
Noprth Chicago, IL 60064

1 Military Assistant for Training and
Personnel Technology
Office of the Under Secretary of Defens
for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301

1 Col. Van Poznak
HQ, MEPCOM
ATTN: Director MEPCAM
2500 Green Bay Raod
North Chicago, IL 60064

1 Dr. W. Steve Sellman
Office of the Assistant Secretary
of Defense (MRA & L)
2B269 The Pentagon
Washington, DC 20301

Department of Defense

1 Mr. John Stryker
HQ, MEPCOM
MEPCAM
2500 Green Bay Road
North Chicago, IL 60064

1 Major Jack Thorpe
DARPA
1400 Wilson Blvd.
Arlington, VA 22209

1 Dr. Robert A. Wisher
OUSDRE (ELS)
The Pentagon, Room 3D129
Washington, DC 20301

BEST COPY AVAILABLE

Civilian Agencies

1 Dr. Bob Frey
Commandant (G-P-1/2)
USCG HQ
Washington, DC 20593

1 Dr. Vern W. Urry
Personnel R&D Center
Office of Personnel Management
1900 E Street NW
Washington, DC 20415

1 Mr. Thomas A. Warm
U. S. Coast Guard Institute
P. O. Substation 18
Oklahoma City, OK 73169

1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Private Sector

1 Dr. James Algina
University of Florida
Gainesville, FL 326

1 Dr. Erling B. Andersen
Department of Statistics
Studiestraede 6
1455 Copenhagen
DENMARK

1 1 Psychological Research Unit
NBH-3-44 Attn
Northbourne House
Turner ACT 2601
AUSTRALIA

1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450

1 Dr. Menucha Birenbaum
School of Education
Tel Aviv University
Tel Aviv, Ramat Aviv 69978
Israel

1 Dr. Werner Birke
Personalstammamt der Bundeswehr
D-5000 Koeln 90
WEST GERMANY

1 Dr. R. Darrell Bock
Department of Education
University of Chicago
Chicago, IL 60637

1 Dr. Robert Brennan
American College Testing Programs
P. O. Box 168
Iowa City, IA 52243

1 Dr. Paul Brower
FEDSIM/NA
6118 Franconia Road
Alexandria , VA 22310

1 Bundministerium der Verteidigung
-Referat P II 4-
Psychological Service
Postfach 1328
D-5300 Bonn 1
F. R. of Germany

BEST COPY AVAILABLE

Private Sector

1 Dr. Ernest R. Cadotte
307 Stokely
University of Tennessee
Knoxville, TN 37916

1 Dr. John B. Carroll
409 Elliott Rd.
Chapel Hill, NC 27514

1 Dr. Kenneth E. Clark
President
Center for Creative Leadership
5000 Laurinda Dr.
P. O. Box P-1
Greensboro, NC 27402

1 Dr. Norman Cliff
Dept. of Psychology
Univ. of So. California
University Park
Los Angeles, CA 90007

1 Dr. Hans Crombag
Education Research Center
University of Leyden
Boerhaavelaan 2
2334 EN Leyden
The NETHERLANDS

1 CTB/McGraw-Hill Library
2500 Garden Road
Monterey, CA 93940

1 Dr. Dattpradad Divgi
Syracuse University
Department of Psychology
Syracuse, NE 33210

1 Dr. Hei-Ki Dong
Ball Foundation
Room 314, Building B
800 Roosevelt Road
Glen Ellyn, IL 60137

1 Dr. Fritz Drasgow
Department of Psychology
University of Illinois
603 E. Daniel St.
Champaign, IL 61820

1 Dr. Susan Embertson
PSYCHOLOGY DEPARTMENT
UNIVERSITY OF KANSAS
Lawrence, KS 66045

Private Sector

1 ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

1 Dr. Benjamin A. Fairbank, Jr.
McFann-Gray & Associates, Inc.
5825 Callaghan
Suite 225
San Antonio, TX 78228

1 Dr. Leonard Feldt
Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

1 Dr. Richard L. Ferguson
The American College Testing Program
P.O. Box 168
Iowa City, IA 52240

1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850

1 Univ. Prof. Dr. Gerhard Fischer
Liebiggasse 5/3
A 1010 Vienna
AUSTRIA

1 Professor Donald Fitzgerald
University of New England
Armidale, New South Wales 2351
AUSTRALIA

1 Dr. Dexter Fletcher
University of Oregon
Department of Computer Science
Eugene, OR 97403

1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 Dr. Robert Glaser
Learning Research & Development Center
University of Pittsburgh
3939 O'Hara Street
PITTSBURGH, PA 15260

BEST COPY AVAILABLE

BEST COPY AVAILABLE

Private Sector

1 Dr. Bert Green
Johns Hopkins University
Department of Psychology
Charles & 34th Street
Baltimore, MD 21218

1 Mr. David Gurtner
FEDSIM/NA
6118 Franconia Road
Alexandria, VA 22310

1 Dr. Ron Hambleton
School of Education
University of Massachusetts
Amherst, MA 01002

1 Dr. Susan Hardwicke
Rehab Group, Inc.
1360 Rosecrans Street (Suite 1)
San Diego, CA 92106

1 Dr. Delwyn Harnisch
University of Illinois
242b Education
Urbana, IL 61801

1 Dr. Paul Horst
677 G Street, #184
Chula Vista, CA 90010

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
603 East Daniel Street
Champaign, IL 61820

1 Dr. Steven Hunka
Department of Education
University of Alberta
Edmonton, Alberta
CANADA

1 Dr. Earl Hunt
Dept. of Psychology
University of Washington
Seattle, WA 98105

1 Dr. Jack Hunter
2122 Coolidge St.
Lansing, MI 48906

Private Sector

1 Dr. Huynh Huynh
College of Education
University of South Carolina
Columbia, SC 29208

1 Dr. Douglas H. Jones
Advanced Statistical Technologies
Corporation
10 Trafalgar Court
Lawrenceville, NJ 08148

1 Professor John A. Keats
Department of Psychology
The University of Newcastle
N.S.W. 2308
AUSTRALIA

1 Dr. William Koch
University of Texas-Austin
Measurement and Evaluation Center
Austin, TX 78703

1 Dr. Michael Levine
Department of Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61801

1 Dr. Charles Lewis
Faculteit Sociale Wetenschappen
Rijksuniversiteit Groningen
Oude Boteringestraat 23
9712GC Groningen
Netherlands

1 Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

1 Dr. Frederic M. Lord
Educational Testing Service
Princeton, NJ 08541

1 Dr. James Lumsden
Department of Psychology
University of Western Australia
Nedlands W.A. 6009
AUSTRALIA

1 Dr. Gary Marco
Stop 31-E
Educational Testing Service
Princeton, NJ 08451

Private Sector

1 Dr. Scott Maxwell
Department of Psychology
University of Notre Dame
Notre Dame, IN 46556

1 Dr. Samuel T. Mayo
Loyola University of Chicago
820 North Michigan Avenue
Chicago, IL 60611

1 William J. McLaurin
66610 Howie Court
Camp Springs, MD 20031

1 Dr. Barbara Means
Human Resources Research Organization
300 North Washington
Alexandria, VA 22314

1 Dr. Robert Mislevy
711 Illinois Street
Geneva, IL 60134

1 Dr. Melvin R. Novick
356 Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

1 Dr. James Olson
WICAT, Inc.
1875 South State Street
Orem, UT 84057

1 Dr. Jesse Orlansky
Institute for Defense Analyses
1801 N. Beauregard St.
Alexandria, VA 22311

1 Wayne M. Patience
American Council on Education
GED Testing Service, Suite 20
One Dupont Cirle, NW
Washington, DC 20036

1 Dr. James A. Paulson
Portland State University
P.O. Box 751
Portland, OR 97207

1 Dr. Sam Pearson
CACI, Inc. FED.
Department 5921
1815 North Fort Myers Drive
Arlington, VA 22209

Private Sector

1 Dr. Mark D. Reckase
ACT
P. O. Box 168
Iowa City, IA 52243

1 Dr. Thomas Reynolds
University of Texas-Dallas
Marketing Department
P. O. Box 688
Richardson, TX 75080

1 Mr. Ken Rieck
FEDSIM/NA
6118 Franconia Road
Alexandria, VA 22310

1 Dr. Andrew M. Rose
American Institutes for Research
1055 Thomas Jefferson St. NW
Washington, DC 20007

1 Dr. J. Ryan
Department of Education
University of South Carolina
Columbia, SC 29208

1 PROF. FUMIKO SAMEJIMA
DEPT. OF PSYCHOLOGY
UNIVERSITY OF TENNESSEE
KNOXVILLE, TN 37916

1 Frank L. Schmidt
Department of Psychology
Bldg. GG
George Washington University
Washington, DC 20052

1 Lowell Schoer
Psychological & Quantitative
Foundations
College of Education
University of Iowa
Iowa City, IA 52242

1 Dr. Kazuo Shigemasu
7-9-24 Kugenuma-Kaigan
Fujusawa 251
JAPAN

1 Dr. Edwin Shirkey
Department of Psychology
University of Central Florida
Orlando, FL 32816

BEST COPY AVAILABLE

Private Sector

1 Dr. William Sims
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

1 Dr. Peter Stoloff
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

1 Dr. William Stout
University of Illinois
Department of Mathematics
Urbana, IL 61801

1 Dr. Hariharan Swaminathan
Laboratory of Psychometric and
Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

1 Dr. Kikumi Tatsuoka
Computer Based Education Research Lab
252 Engineering Research Laboratory
Urbana, IL 61801

1 Dr. Maurice Tatsuoka
220 Education Bldg
1310 S. Sixth St.
Champaign, IL 61820

1 Dr. David Thissen
Department of Psychology
University of Kansas
Lawrence, KS 66044

1 Dr. Robert Tsutakawa
Department of Statistics
University of Missouri
Columbia, MO 65201

1 Dr. David Vale
Assessment Systems Corporation
2233 University Avenue
Suite 310
St. Paul, MN 55114

Private Sector

1 Dr. Howard Wainer
Division of Psychological Studies
Educational Testing Service
Princeton, NJ 08540

1 Dr. Brian Waters
HumRRO
300 North Washington
Alexandria, VA 22314

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

1 Dr. Donald O. Weitzman
Mitre Corporation
1820 Dolley Madison Blvd
McLean, VA 22102

1 DR. GERSHON WELTMAN
PERCEPTRONICS INC.
6271 VARIEL AVE.
WOODLAND HILLS, CA 91367

1 Dr. Rand R. Wilcox
University of Southern California
Department of Psychology
Los Angeles, CA 90007

1 Wolfgang Wildgrube
Streitkraefteamt
Box 20 50 03
D-5300 Bonn 2
WEST GERMANY

1 Dr. Bruce Williams
Department of Educational Psychology
University of Illinois
Urbana, IL 61801

BEST COPY AVAILABLE

Additional Names

1 Dr. Frank Erwin
President
Richardson, Bellows, Henry & Co.
Suite 612
1140 Connecticut Avenue, NW
Washington, DC 20036

1 Dr. Lorraine Eyde
Office of Personnel Research &
Development Center
1900 E Street, NW
Washington, DC 20415

1 Dr. Milt Hakel
Ord Inc.
2455 N. Star Road
Suite 303
Columbus, OH 43221

1 Dr. Samuel Messick
Vice President for Research
Educational Testing Service
Princeton, NJ 08541

1 Dr. Nancy Petersen
Educational Testing Service
Princeton, NJ 08541

1 Dr. Mary Tenopyr
AT & T
550 Madison Avenue
Room 1141
New York, NY 10022

1 Dr. Alexandra Wigdor
National Research Council
2101 Constitution Avenue, NW
Washington, DC 20418